Optimal Reactive Power Dispatch Using an Improved Genetic Algorithm

Dawood Talebi Khanmiri, Nasibeh Nasiri, and Taher Abedinzadeh

***Abstract*—This paper presents an improved genetic algorithm for Optimal Reactive Power Dispatch (ORPD) to minimize active power loss and improve the voltage profile of power systems. The goal of ORPD is to determine generator bus voltages, transformer tap positions and switchable shunt capacitor banks when satisfying problem constraints such as bus voltage magnitude limits, generator reactive capabilities and the size of shunt capacitors. It is obviously a large-scale nonlinear optimization problem with both continuous and discrete control variables. While Genetic Algorithm is known to reach the global optimal solution, the main difficulty of application of GAs is their premature convergence. In order to improve the search ability of GA this paper proposes a new coding method for this problem in which each chromosome is divided into two sections, one for continuous variables and another for discrete ones. Also appropriate specific crossover and mutation operators that can work with both real and binary genes are defined. The proposed method is tested on IEEE 30-bus and 14-bus systems and results are compared with those of Simple binary-coded and real-coded genetic algorithms. Test results demonstrate the effectiveness of proposed method in finding the global optimal solution within a reasonable computing time.**

***Index Terms*—Improved genetic algorithm, loss reduction, optimal reactive power dispatch, voltage profile improvement.**

I. Introduction

Optimal Reactive Power Dispatch has an important role in secure and economic operation of power systems. Ensuring that voltage at each system busbar remains within its acceptable limits is an essential aspect of maintaining quality and security. Also adjusting system variables so that the transmission loss is minimized does affect overall generation cost. The reactive power dispatch problem is to control generator bus voltages, transformer tap positions and the size of switchable shunt capacitors to minimize the transmission active loss. Solving this optimization problem is subject to some operation constraints including reactive power source capabilities, transformer tap setting limits and voltage magnitude limits of load buses.

ORPD is a nonlinear large-scale nonconvex problem with both discrete and continuous variables and may have several local minima. Many optimization techniques such as linear programming [1] and nonlinear programming [2] are used to solve the problem. However, these conventional methods can easily be caught in a local optimal solution. In recent decades there has been a growing trend towards the application of stochastic search methods to global optimization problems. Simulated Annealing [3], Evolutionary Programming [4] and Genetic algorithm [5-10] has been applied to solve the ORPD problem.

One particular advantage of using a GA-based approach is that GA works with coded strings of parameters rather than parameters themselves. So it can work with real, binary and integer variables. In simple GA all variables are coded in binary format increasing the chromosome size due to achieve an acceptable resolution for real variables. It results in excessive computation time. By contrast, in real coded GA all variables are considered as continuous real ones. In this case a discrete variable such as the size of a shunt capacitor can take any value but practical considerations may dictate that it should be selected from a list of standard sizes, and the solution needs to be converted to a physically implementable one and this may lead to a solution that is not optimum or cause some constraints not to be satisfied.

This paper proposes an improved genetic algorithm in which each chromosome is divided into two sections, one for continuous variables and another for discrete ones. Also, appropriately, specific crossover and mutation operators which act differently in two sections are defined. The proposed Improved GA is tested on IEEE 14-bus and 30-bus systems and test results are compared with those of the Binary and Real GAs. It is shown that proposed IGA has more capability of finding the global optimal solution within reasonable computing time

II. Problem Formulation

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network which can be described as follows:

$$f = \sum_{k\in BR} P_{k\,Loss} = \sum_{k\in BR} g_k (V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij} \quad (1)$$

where k refers to the branch between buses i and j. $P_{k\,Loss}$ and g_k are active loss and mutual conductance of branch k, respectively. V_i, V_j and θ_{ij} are voltages of buses i and j and phase angle difference between them, respectively.

The equality constraints are active and reactive power equalities. The inequality constraints are bus voltage, generator reactive power, shunt capacitor reactive power and transformer tap position constraints.

$$P_{Gi} - P_{Di} = V_i \sum_{j\in B} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0 \quad (2)$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{j\in B} V_j \left(G_{ij}\sin\theta_{ij} + B_{ij}\cos\theta_{ij}\right) = 0 \quad (3)$$

$$V_{i\,min} \le V_i \le V_{i\,max} \qquad i \in B \quad (4)$$

$$T_{k\,min} \le T_k \le T_{k\,max} \qquad i \in BRK \quad (5)$$

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$$Q_{Gi\,min} \leq Q_{Gi} \leq Q_{Gi\,max} \quad i \in BG \qquad (6)$$
$$Q_{Ci\,min} \leq Q_{Ci} \leq Q_{Ci\,max} \quad i \in BC \qquad (7)$$

where P_{Gi} and Q_{Gi} are active and reactive power supply of bus i, P_{Di} and Q_{Di} are bus active and reactive load, G_{ij} and B_{ij} are mutual conductance and susceptance between bus i and j, T_k transformer tap in branch k, Q_{Ci} is reactive power of shunt capacitor in bus i, B is the set of system buses, BG is the set of generator buses, BC is the set of buses with shunt capacitor and BRK is the set of transformer branches. Indices min and max indicate upper and lower limits of variables.

The equality constraints and generator reactive power limits are satisfied by load flow calculation, tap position and capacitor reactive power constraints can be easily satisfied by creating feasible solutions in GA. Bus voltage constraint is combined into the fitness function as a penalty term. This is due to this fact that many bus voltages approach their limits to reduce cost, but this situation tend to stress the system and decrease its security under any unforeseen contingencies.

The problem is generalized as follows:

$$F = f + \sum_{i \in BPQ} \lambda_i (\Delta V)^2 \qquad (8)$$

where λ_i is the penalty factor and ΔV is the bus voltage violation from its limits.

III. Genetic Algorithms

GAs are powerful search algorithms based on mechanics of natural selection, where they gradually evolve a set of initial poor solution guesses to a set of better solutions. GAs are robust and parallel algorithms that theoretically can reach the global optimal point.

Basically a simple GA works with a string of binary digits representing a coding of control parameters of a given problem. Correspondingly, Genetic operators act on binary strings. In this coding method it is necessary to devote enough bits to continuous parameters to obtain an acceptable resolution. For example in this paper 11 bits are devoted to each generator bus voltage. When the number of continuous variables is large chromosome will be very long in this coding method and it can increase the computation time dramatically.

On way to reduce the chromosome size is to use a real number for each control variable. It decreases the computation time but for discrete parameters, when applying it in practice, we have to round it to a discrete feasible value. This may lead to a solution that is not optimum or cause some violations from constraints like bus voltages.

A. Proposed Improved Genetic Algorithm

Considering advantages and shortcomings of binary and real coding, this paper proposes a mixed coding of control variables. In this method continuous variables with real values and discrete parameters with binary codes comprise the string of control variables used by IGA. As shown in Fig. 1 the chromosome consists of two sections, one section for continuous variables and another for binary parameters. This coding avoids unnecessarily increasing chromosome size while considering capacitor sizes and transformer tap positions as feasible discrete variables.

B. Review Stage

Proposed mixed coding requires new appropriate crossover and mutation operators. These operators could act differently in various parts of the chromosome based on the performance which operators have in dealing with binary-coded or real- coded variables.

Until now many crossover operators for both binary and real coding such as single point, multipoint, scattered or heuristic crossover have been presented in the literature.

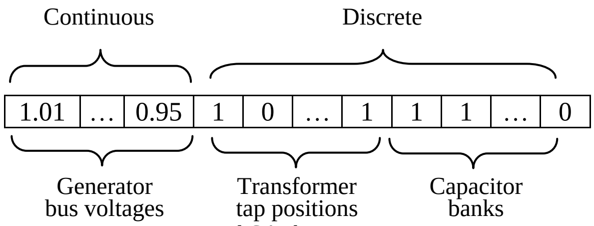


Fig. 1. Proposed GA chromosome structure.

Proposed heuristic-scattered crossover operator uses heuristic crossover in the real section and scattered crossover in binary section. Heuristic crossover returns a child that lies on the line containing the two parents, a small distance away from the parent with the better fitness value in the direction away from the parent with the worse fitness value. Scattered crossover creates a random binary vector and selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. Fig. 2 shows the proposed crossover operator. First a random vector of 0 and 1 bits is created with the same length as the binary substring of chromosome. Then it forms the binary substring of child as described above. For the real substring, child is produced as below:

$$Child = Parent2 + R \times (Parent1 - Parent2) \qquad (9)$$

where parent1 is better than parent2 and R is the closeness ratio and indicates how far the child is from the better parent.

Parent 1	1.00	0.95	0	1	0	0	1	0
Parent 2	1.01	0.90	1	1	1	0	1	0
Random string			1	0	0	1	0	1
Child	0.998	0.96	0	1	1	0	1	0

Fig. 2. Proposed crossover operator

While the crossover is the main genetic operator exploiting the information included in the current generation, mutation is responsible for the injection of new information and avoiding premature convergence to a local optimal point.

Mutation operator selects a string at random and creates a binary vector. Then it changes genes in the string wherever the vector is 1. In the binary substring it changes a 1 to a 0 or vice versa and in the real substring it replaces the gene by a random number within acceptable range. Mutation probability is normally small. Its initial value is 0.1 but it shrinks in each generation until it reaches 0 at the last generation. It enables algorithm to explore a vast area at the beginning while searching around optimal point accurately in the last generations. Fig. 3 shows the proposed mutation operator.

Parent	1.00	0.95	1	1	0	1	0	1
Random string	1	0	0	0	0	1	0	0
Child	1.09	0.95	1	1	0	0	0	1

Fig. 3. Proposed mutation operator

IV. Simulation Results

The proposed IGA for reactive power dispatch is evaluated using the IEEE 30-bus and 14-bus test systems.

A. IEEE 30-Bus System

The IEEE 30 bus, 41-branch system has 13 control variables: 6 generator bus voltages, 4 transformer tap settings and 2 shunt capacitor buses, as shown in Fig. 4. Control variables, their limits and number of bits devoted to them in the chromosome are given in Table I. It is assumed that active power generation of each generator is determined by an optimal power flow [11]. Total active power loss is 9.470 MW and all bus voltages are within their limits.

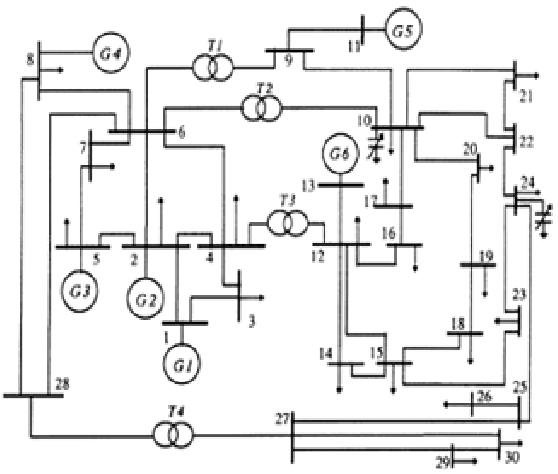


Fig. 4. IEEE 30-bus test system

TABLE I: Control Variables in the IEEE 30-bus System

Variable	Limits [pu]	Steps [pu]	Number of bits		
			Binary	Real	Proposed
Generator bus voltage	0.9-1.1	-	6×11	6×1	6×1
Transformer tap position	0.9-1.1	0.01	4×5	4×1	4×5
Capacitor reactive power	0-0.15	0.05	2×2	2×1	2×2
Chromosome length			90	12	30
Average computation time [s]			108.6	56.5	60.2

In all GAs in this paper, a constant population size of 20 individuals is used with maximum generation of 300 as a stopping criterion. In order to mitigate the effect of the probabilistic nature of GA on results the algorithms are executed 30 times when applied to a test system. The best and worst results, the average of results and the average computation time for each GA are shown in Table I. Also Table III lists the best control variables found by IGA and other two GAs.

TABLE II: Simulation Results for the IEEE 30-bus System

		Binary	Real	Proposed
Active Power Loss [MW]	Best	9.000	9.035	8.989
	Worst	9.153	9.494	9.159
	Average	9.066	9.196	9.0355
Maximum Saving [%]		4.96	4.59	5.08
Average Computation Time [s]		108.6	56.5	60.2

TABLE III: The best Control Variables for the IEEE 30-bus System

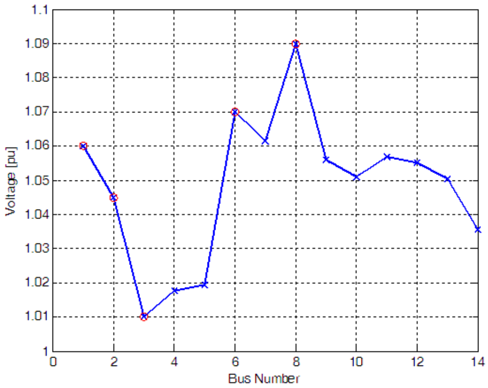
Variable		Binary	Real	proposed
Generator Bus Voltage [pu]	**V1**	1.0840	1.0822	1.0791
	V2	1.0674	1.0632	1.0608
	V3	1.0375	1.0371	1.0298
	V4	1.0414	1.0988	1.0347
	V5	1.0680	1.0736	1.0603
	V6	1.0000	0.9132	1.0746
Tap Position [pu]	**T1**	1.07	1.03	1.03
	T2	0.90	0.96	0.92
	T3	0.95	0.96	1.00
	T4	0.98	0.98	0.97
Capacitor [MVar]	**C1**	15	15	15
	C2	15	15	10

It is shown from the results in Table II that proposed IGA finds better solutions for reactive power dispatch problem than do other two GA presented in this paper. Better solution found by IGA leads to lower active power loss and better voltage profile. Also it is that computation time is quite acceptable for proposed IGA. For real-coded GA six solutions out of 30 did not satisfied bus voltage limits after rounding the discrete variables to applicable values. These solutions were not considered in calculating average

B. IEEE 14-bus system

The IEEE 14-bus test system has 9 control variables including 5 generator bus voltages, 3 transformer tap settings and one shunt capacitor buses. The network total active power loss is 13.393 MW. In this simulation Bus voltage limits are defined as 0.95 and 1.05 for load buses to achieve a better voltage profile. Assuming these limits, some buses have voltages above upper limit before reactive power dispatch.

Proposed IGA is applied to optimize reactive power dispatch in this test system. It can adjust the control variables so that total power loss decreases to 12.515 MW which equals to % 6.56 saving. Also it results in a voltage profile that there is no violation from voltage limits in load buses. It can be seen from Fig. 5 that voltage profile is improved after applying the optimal settings found by IGA.



(a)

Fig. 5. Voltage profile of the IEEE 14-bus system (a) before (b) after reactive power dispatch. o: PV Buses; ×: Load Buses

V. Conclusion

An Improved Genetic Algorithm is proposed to solve optimal reactive power dispatch problem. In the proposed IGA a mixed coding of control variables is used to cope with both continuous and discrete variables. Correspondingly appropriate genetic operators which can work with real and binary genes in the chromosome are proposed.

The proposed IGA was tested using IEEE 30-bus and 14-bus test systems. Simulation results show that the IGA decreases active power loss while improving the voltage profile of the power system. Also, compared to binary-coded and real-coded GAs, it produces better solutions within acceptable computation time.

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